# Mapping Shorelines in Puget Sound I: A Spatially Nested Geophysical Shoreline Partitioning Model

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## Introduction

The ecology of nearshore benthos (from intertidal to water depths of 10 m) has been studied in detail in many locations in the U.S., and our understanding of nearshore biological and physical processes has increased substantially. Many of the individual processes structuring nearshore communities, such as wave energy, substrate size, competition and predation have been extensively examined and are reported in the literature (Schoch, 1996). We do not know how the many processes that affect community structure interact over different scales of space and time. The complexities of these interactions may confound our understanding. However, it is clear that there are strong physical and biological linkages (Schoch and Dethier, 1996). These linkages force predictable patterns of biological communities and intertidal habitats. Determining why communities change over space and time is still a significant challenge but the patterns observed in the data can be used to predict community structure so that changes can be quantified.

Many organisms within marine ecosystems are sensitive to environmental changes or gradients and may serve as indicators of environmental health. Detecting change in biological communities is an inherent part of experimental ecological research and applied monitoring programs. Many scientists and resource agencies have attempted to monitor localized intertidal and subtidal transects in hopes of finding a short–term experimental response or a long–term indicator of ecosystem health. Long–term monitoring presumably will provide a statistical baseline from which a change can be detected. However, the dynamic nature of the marine environment causes high spatial and temporal variation in organism abundances and community structure, and generally confounds our ability to detect non–catastrophic perturbations. Biological data from intertidal monitoring stations are plagued by two fundamental problems. The first is the large temporal variability of organism abundances in natural ecosystems which masks our ability to statistically separate an actual change caused by a perturbation (the signal) from natural cycles (the noise). The second issue is a scaling problem. Extrapolating or generalizing the results of localized studies to broad areas is statistically fraught with problems. We describe here the application of a model (Shoreline Classification and Landscape Extrapolation: SCALE) that increases biological homogeneity by partitioning a shoreline into a spatially nested series of geophysically uniform segments (Schoch and Dethier, in review). By then statistically aggregating similar but spatially separated units, we can scale up localized biological data to larger regions. This knowledge is important for resolving many scientific and resource management issues in Puget Sound.

## Methods

The site selected for this study was Carr Inlet (including Henderson Bay), the first major embayment south of the Tacoma Narrows in the Puget Sound estuary.

At all spatial scales the primary environmental determinants of intertidal organism abundance and community structure are substrate size (e.g., bedrock vs. gravel vs. sand etc.) and immersion time (or elevation above low water). Substrate size determines the stability (movement potential) and dynamism (movement frequency), both factors in community disturbance. Solid surfaces generally preclude infauna, while dynamic mobile substrates preclude most sessile organisms. Many mobile but low dynamism substrates (e.g., mud) are extremely rich in biota, especially infauna. Sediment size and dynamism also affect moisture retention, $O_2$ content, and organic content. The position or elevation within the intertidal zone leads to differences in immersion times, which result in distinctive community zonation patterns.

Another key physical feature is wave energy, which affects community structure both directly through episodic disturbance events and indirectly by controlling substrate dynamics over short and long temporal periods. The magnitude of wave runup or swash can also affect community structure by elevating zonation levels, delivering nutrients and preventing desiccation. In relatively protected areas such as Carr Inlet, wave runup is practically non-existent and large waves are infrequent, such that wave energy does little to directly structure the intertidal community. However, indirect effects include current propagation and substrate movement over long temporal scales. In Carr Inlet, the processes of sediment suspension and transport can be expected to occur primarily during the winter when strong southerly winds blow along the axis of the bay.

Partitioning within Carr Inlet of 1–10 km long shoreline blocks was based on gradients of salinity and water temperature, and the location of major sediment plumes. Night-time imagery from the Advanced Very High Resolution Radiometer (AVHRR) satellite sensor (band 4, 1 km resolution obtained from the National Environmental Satellite Data and Information Service) provided a large scale temporal data series of sea surface temperature (SST). These data showed a consistent (over a three-year annual interval) temperature gradient from the cold deeper water in outer Carr Inlet to the warmer shallow water of inner Henderson Bay. LandSat 5 data from bands 1, 2, and 3 were used to locate sediment plumes, areas of urban, suburban, timber, and agricultural development, and for measuring wave fetch at scales of 1–10 km. The only significant sediment plume identified emanates from Burley Lagoon and flows along the eastern shoreline. Field measurements of sea surface temperature and conductivity near the shore were made over a two–day period with a hand held instrument at 14 sites, spaced approximately five km apart. Salinity was calculated from these measurements.

The above 10-km blocks or quadrants of Carr Inlet were partitioned into 100–1,000 m preliminary segments based on photogrammetric analyses of the principal shoreline geomorphology. The shore type was classified according to a system used for resource management in British Colombia (Howes et al., 1994). Low altitude color infrared (CIR) aerial photographs (1:13,000 scale), flown at an extreme low tide, were used to differentiate well drained or coarse substrates (high radiance) such as pebbles and cobbles from saturated or fine substrates with high moisture content (low radiance) such as silt and sand. The CIR photography was also used to delineate the intertidal zone from the uplands using the strong chlorophyll signature of terrestrial plants. The lower intertidal boundary was also shown clearly due to the dark body properties of water at infrared wavelengths. The digitized intertidal zone map was used in a GIS to calculate areas and dimensions of shore partitions.

The geomorphic shore segments described above were then refined by ground surveys to further partition the shoreline, in both the alongshore and across–shore, according to beach slope and substrate sizes (primary, secondary, and interstitial). Geophysically homogeneous alongshore segments (10–100 meters in length) were identified in the field and delineated on orthophoto basemaps during the spring low tides from April 8–11, 1997. Each alongshore segment was vertically separated into four across–shore polygons centered at specific elevations that correspond to immersion times during the daily tidal cycle, based on the mean tidal statistics for Carr Inlet.

Table 1 lists the attributes and spatial scales used for shoreline segmentation. Substrate size was measured according to the Wentworth particle size classification for the following percent cover categories: primary (for particles comprising more than 60% of the substrate), secondary (for particles less than 40% of the substrate), and interstitial. Beach slope was measured with a hand held digital inclinometer. Substrate permeability and groundwater salinity were measured in the lower intertidal zone by digging a hole to 0.3 m and inserting a perforated bucket. Permeability was quantified by the time required to fill the bucket with ground water, and salinity was measured *in situ*. Substrate roughness was qualitatively categorized based on the degree of armoring. Groundwater seepage was estimated as a percentage of the polygon length exhibiting seepage from the beach prism based on photogrammetric interpretation of CIR aerial photos. Dynamism is the relative bed stability calculated using predicted wave velocities. The effect of waves on beaches is best represented by surf characteristics.

The Iribarren number was calculated for each across–shore polygon since slope angles vary considerably across most segments: an upper intertidal seawall is generally highly reflective and a lower intertidal sand flat is highly dissipative.

Table 1. Geophysical attributes of the SCALE shoreline partitioning model.

| Qualitative | Quantitative (except where noted) | | | |
|---|---|---|---|---|
| Shoreline Type (100–1,000 m) | Block (1–10 km) | Segment (10–100 m) | Polygon intertidal zone | |
| substrate size | salinity | aspect | surf parameter | (calculated) |
| slope angle | surface temperature | drift exposure | slope | |
| geomorphological form | average fetch | wave energy | dynamism | (calculated) |
| | | | roughness | (qualitative) |
| | | | substrate size: | |
| | | | | primary grains |
| | | | | secondary grains |
| | | | | interstitial grains |
| | | | permeability | |
| | | | seepage | (qualitative) |

There are few published wave statistics for this area, so for each segment we derived the required parameters from measurements of maximum fetch, or the longest overwater distance unimpeded by a landmass (obtained from a GIS coverage of the South Sound). We classified each distance measurement and estimated the wave statistics for each fetch class (Table 2) from graphs published in the Shore Protection Manual (CERC, 1984).

Segment polygons for each intertidal level were aggregated separately using a combination of multivariate hierarchical agglomerative clustering and sorting to produce relatively similar groups. The large number of segments (310 in about 56 km of shoreline) in the project area was an indicator of local shoreline heterogeneity, most of which was explained by differences in wave energy (surf similarity) and substrate particle size (primary and secondary). These variables and dynamism (substrate stability) were assumed the most important, or primary, determinants of community structure. The remaining variables, considered of secondary importance, include permeability and roughness (which co–vary with particle size), interstitial particle size and groundwater seepage. The primary variables were given more weight by separately clustering the secondary variables and then adding the resulting secondary group variable to the smaller matrix of primary variables. Each matrix was relativized by column maximum values to equalize the various measurement scales, then clustered using Sorenson's city block distance and the centroid linkage method. The centroid method was selected for providing the best separation of clusters, but since it is space–contracting, there is a chance that polygons may become part of a growing cluster when they should have formed the nucleus of a new cluster. An alternative would be to use a space–conserving method such as the group mean linkage, but results from preliminary trials produced a large number of small clusters with few natural groupings. We used Wishart's objective function (1969) to evaluate the amount of information lost at each step of aggregation. The dendrograms showed that 95% of the segments were clustered before 25% of the information was lost according to this evaluation function. Using Wishart's 25% as the clustering cutoff, 20 groups were selected for the secondary group cutoff and 12 for the primary grouping. Primary cluster group membership was evaluated using direct discriminant function analysis to determine the probability of correct classification for each across–shore polygon.

Table 2. Wave parameters derived for calculating the surf similarity index.

| Fetch Distance (km) (CERC) | Sustained Wind Speed (kts) (CERC) | Significant Wave Height (m) (CERC) | Wave Period (s) (CERC) | Wave Length (m) | Energy Category (SCALE) | |
|---|---|---|---|---|---|---|
| <0.1 | 5 | 0.1 | 1 | 1 | 1 | sheltered |
| 0.1–0.5 | 10 | 0.2 | 1.5 | 2 | 2 | |
| 0.5–1 | 10 | 0.3 | 2 | 6 | 3 | protected |
| 1–5 | 20 | 0.4 | 2.5 | 10 | 4 | |
| 5–10 | 20 | 0.5 | 3 | 14 | 5 | semi–protected |
| 10–50 | 30 | 1 | 4 | 25 | 6 | |
| 50–100 | 30 | 2 | 5 | 40 | 7 | semi–exposed |
| 100–500 | 40 | 3 | 6 | 60 | 8 | |
| 500–1000 | 40 | 4 | 8 | 100 | 9 | exposed |
| >1000 | 50 | 5 | 10 | 150 | 10 | |

# Results

Based on the results of the AVHRR data analysis, the field measurements of SST, salinity, and measurements of wind fetch, Carr Inlet was subdivided into four spatial blocks (quadrants) to reduce the effects of these gradients. Block extent was visually determined from GIS overlays of these data. While these gradients undoubtedly vary seasonally, the AVHRR imagery showed spring and summer trends for SST that were sufficiently consistent from year to year (May 1995–May 1997) to justify spatial blocking.

Photogrammetric segmentation by shore type generated 23 partitions, with three principal substrate types represented (mud, sand, and gravel). Mud shores were typically low angle and sheltered, with a low radiance signature indicating relative impermeability. Sand beaches had a higher radiance with a smooth texture and often showed well developed bars and troughs over the low tide terraces. The "gravel" substrate is a complex and highly variable mix of small boulders and cobbles overlying gravel, sand, and mud, with occasional areas of hardpan (consolidated clays). These show as high radiance textured features on the CIR imagery. Generally the beaches in the project area are vertically complex with the upper zone substrate being different from the middle and lower zones. Characterization at this spatial scale was based on the substrate type with the largest surface area for a given segment.

The ground surveys delineated 310 alongshore segments, composed of 1227 across–shore polygons (309 upper, 304 upper–middle, 313 lower–middle, 301 lower: "missing" polygons occurred, for example, in the shallow inlets where there was no low zone). The cluster analysis forced each across–shore polygon into one of 12 groups (12 clusters for each of three zones). Figure 1 shows the distribution of segment clusters in terms of the number of segments per cluster and the percent of shoreline length represented by each group. Spatially dominant habitats in the upper–middle zone are the clusters 1 (semi–protected pebbles), and 2 (protected sand and pebbles), representing 60% of the project shoreline. The lower–middle zone has three spatially dominant clusters (1 is protected pebbles, cobbles and sand; 2 is protected pebbles and cobbles; and 3 is protected pebbles), representing 64% of the shoreline length. The lower zone habitats are somewhat more evenly distributed, but four clusters still dominate (cluster 3 is semi–protected sand; 4 is protected sand and silt; 5 is protected sand, pebbles, and mud, and cluster 8 is mostly sheltered silt) with 58% of the shore length.

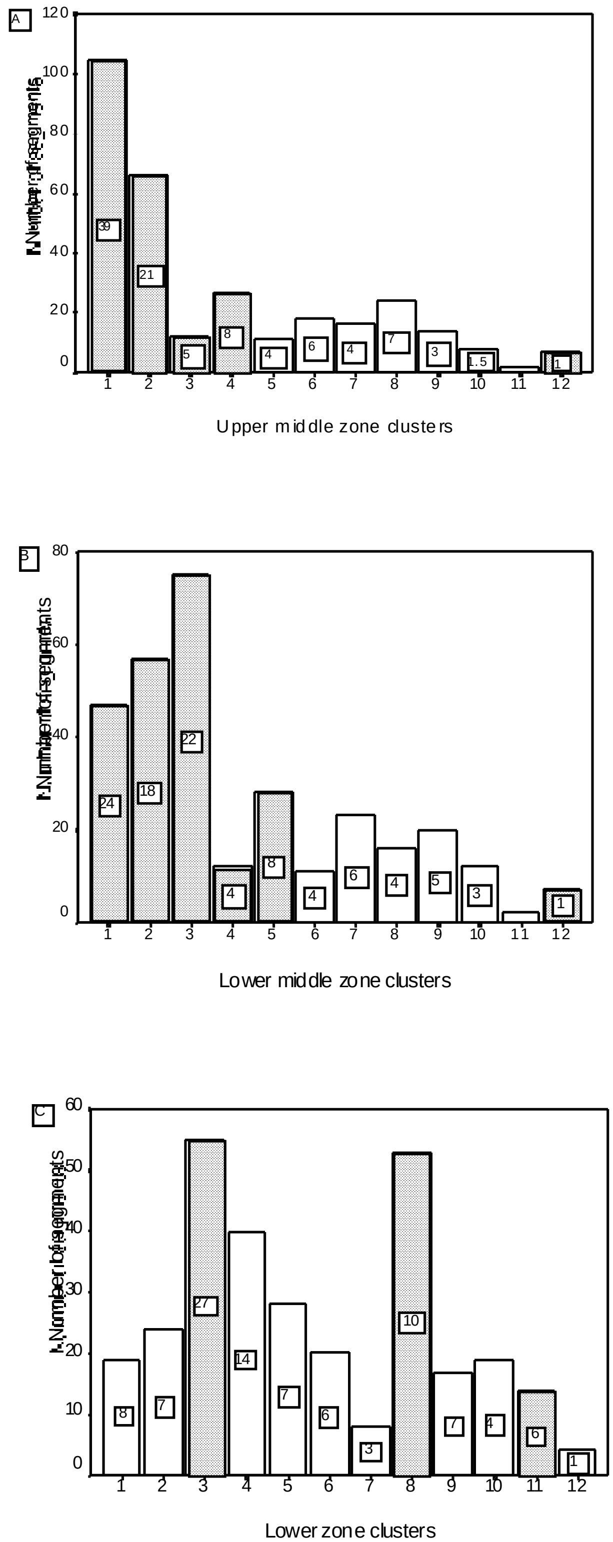


Figure 1. Distribution of intertidal habitat types represented by clusters of shoreline segments. The height of each bar represents the number of segment members for each cluster and the number inset on the bar is the percent of shoreline length represented by each. The shaded bars are those clusters where biota were sampled from a random selection of segments.

The cluster membership identifier and the spatial block designator were added to the geophysical data matrix, and the database was sorted resulting in subgroups of polygons nested within each spatial block. The biological sampling design was centered around these analysis groups (Figure 2; see Dethier and Schoch, this volume). The subset of cluster segment members within a spatial block are referred to by the most general classification category of either mud, sand, or gravel shoreline types. In most cases the polygon substrate is considerably more complex. For example, the upper–middle and lower–middle zones for both the "sand" and "gravel" shoreline segments were characterized by cobbles and pebbles, usually with interstitial sand or with underlying hardpan. Because exact physical matches for all zones among segments were unlikely, priority was given to matching the lower zones (there is some variation within groups in substrate type and seepage, especially in the middle zones for the mud and sand groups).

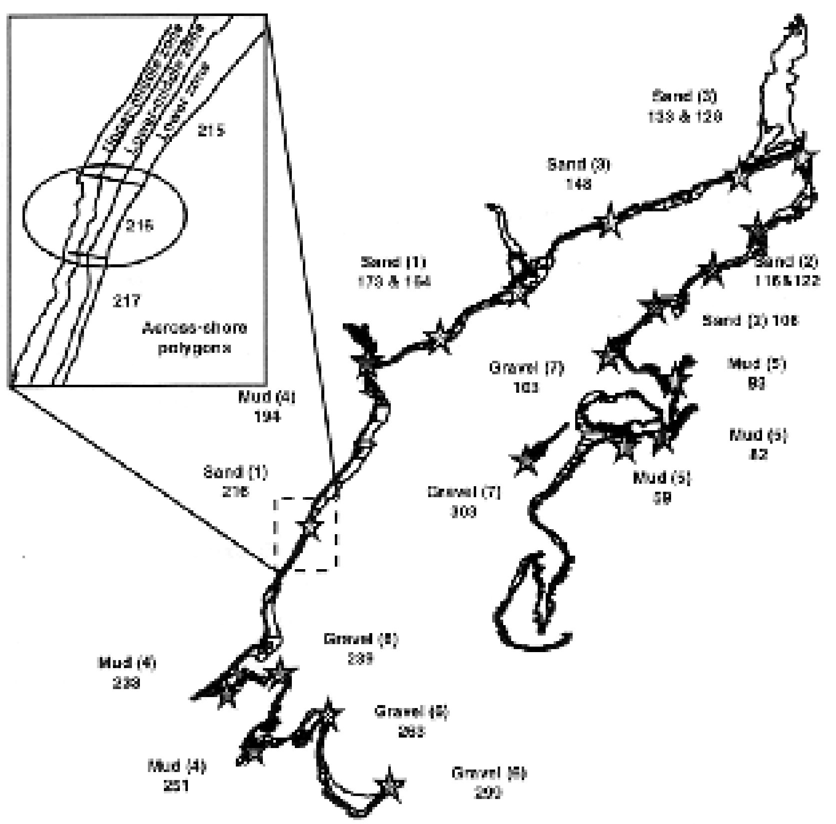


Figure 2. Map of the Carr Inlet intertidal zone (part of a GIS database) illustrating the spatial distribution of the shore polygons. Detailed partitioning is shown for Segments 215–217 in the enlarged inset. The stars show the locations and numbers of shore segments randomly selected for biotic sampling, the analysis group number in parentheses, and the general shore type.

# Conclusions

Our ability to evaluate the scale and consequences of changes in the ocean's biodiversity due to human activities is seriously compromised by critically inadequate knowledge of the patterns and the basic processes that control the diversity of life in the sea. Studies applied to the nearshore are helping to define the patterns and the processes influencing marine biodiversity. If the biogeochemical processes determining patterns in nearshore habitats can be defined as proposed by this study, then predictions can be made about community structure over many scales of space and time. This model has application to oil spill damage assessments, inventory and monitoring programs, global change, and biodiversity studies. Additional applications can be explored in hindcasting the ecological functions of disturbed habitats for mitigation and restoration projects, in forecasting impacts based on trends in human or natural perturbation patterns, and in site selection for experiments in community ecology.

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